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Multi-Level Planning and Scheduling for Parallel PCB Assembly Lines Using Hybrid Spider Monkey Optimization Approach

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ABSTRACT Printed circuit board (PCB) assembly lines are significant to produce a variety of electronic products. PCB manufacturing industries tend to move towards automated and complex manufacturing system due to an increase in the customer demand for more sophisticated products. PCB assembly process involves highly interrelated levels of planning and scheduling problems. Therefore, the current research investigates multi-level planning and scheduling of PCB assembly lines, which include line assignment to the PCB models, component allocations to machines, and component placement sequencing by machines on PCB boards. A mixed integer-programming model is developed to integrate the planning and scheduling problem of parallel PCB assembly lines to maximize the net profit. A hybrid spider monkey optimization (HSMO) algorithm is proposed to solve the multi-level planning and scheduling problem. The performance of the proposed HSMO algorithm is compared to artificial bee colonial (ABC), genetic algorithm (GA), particle swarm optimization (PSO), and simulated annealing (SA) algorithms. Moreover, the proposed HSMO algorithm is validated against ABC, GA, PSO, and SA algorithms with the case problem taken from well-reputed PCB manufacturing industry in China. The computation experiments indicate that the proposed HSMO algorithm can achieve good near-optimal solutions when compared with the other-mentioned four algorithms based on performance and efficiency for benchmark problems and real case problem.

INDEX TERMS Hybrid spider monkey optimization, multi-level problems, parallel assembly lines, planning and scheduling problems, printed circuit board.

I. INTRODUCTION

PCB boards are used in a variety of electronic products from small mobile phones and computers to large and more sophisticated aircraft and space shuttles. In recent years, the demand of PCBs has been increased significantly [1]–[3]. In today's technology enhancement era, electronic products need more improvement in their functions with minimal size to use them in smart systems. To cope with this issue, more sophisticated, innovative, and cost-effective production techniques are required. Steps involved in PCB manufacturing process to convert raw material into the final product are shown in Figure 1. In PCB assembly process, the component placement using SMT machines is the most critical stage [4]; therefore, it is focused in the current research. Moreover, there are various planning and scheduling decision problems in PCB assembly process, i.e., PCB Line Assignment Problem (LAP), Components Allocation Problem (CAP) and Components Placement Sequence Problem (CPSP). These problems are being faced at different level of planning hierarchy as indicated in Figure 2.

In recent years, industries are using parallel PCB assembly lines with different capacities and number of machines [5]; therefore, all the planning problems are significant to investigate. It can be seen from Figure 2 that planning problems are categorized in three different levels, in level 1 PCB boards

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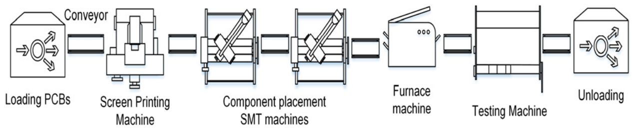

FIGURE 1. PCB manufacturing processes.

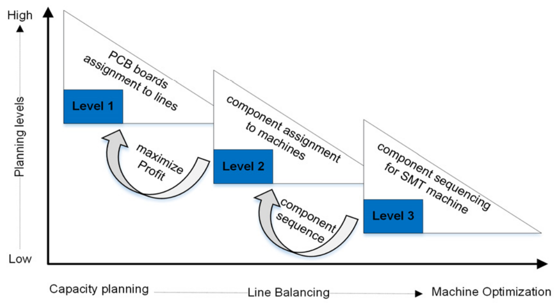

FIGURE 2. Planning hierarchy for PCB problem.

are assigned to the PCB assembly lines, in level 2, the components are assigned to the machines in each PCB assembly line, and in level 3, the components sequence is determined for PCB boards on the SMT machines. To synchronize the customer demands and planning of various levels of the PCB assembly lines (PCBALs), Rogers and Warrington [6] proposed a hierarchal method. The line assignment problem (LAP) has been investigated in literature with different objectives, i.e., minimize the makespan, cycle time, setup time, line capacity and workload balancing using heuristics and mixed integer linear programming [2], [7]. Neammanee and Randhawa [8] has investigated the LAP for high and low volume production and multiple tasks of PCB boards on the assembly line to minimize the makespan. Ellis and Bhoja [9] formulated a mixed integer linear programming (MILP) model to solve LAP using branch and bound algorithm.

The Level 2 problem is related to the allocation of components to different SMT machines and is known as component allocation problem (CAP). Components allocation to the SMT machines is significant because the optimum allocation of components is required to balance the workload of the assembly line identical to standard assembly line balancing problems. Torabi *et al.* [10] formulated a MILP model for CAP to minimize the processing cost and machine set-up times using a heuristic method. Lee and Kim [11] developed MILP model for CAP to balance the workload among the SMT machines in the assembly line using heuristic methods. Ji *et al.* [12] formulated the MILP to solve CAP for production of high-volume orders to minimize the cycle time using genetic algorithm.

The level 3 problem is related to the component placement sequence problem (CPSP), in which pick and place operation is performed for placement of components on the PCB boards. In a mass production system, CPS is considered as the bottleneck process in the PCBALs. Zhu and Zhang [13] extracted from their studies that solving CPSP could significantly increase the performance of PCBALs. Neammanee and Randhawa [8] and Ho and Ji [7] addressed that CPSP is a lower level planning problem in which machines are required to optimize the placement sequence of the allocated components. In literature, various methods have been studied by different researchers, i.e., Zhu and Zhang [13] proposed an improved Shuffled Frog-leaping Algorithm and Shih [14] to solve CPSP in SMT machines. Eusuff *et al.* [15] studied CPSP and feeder location problem of SMT machine to optimize using the Shuffled frog-leaping algorithm. Dengiz and Akbay [16] designed a simulation model to minimize the cost and maximize the profit in PCB production line. He *et al.* [17] worked on placement of a large number of tiny components on the surface of PCB and designed a multi-phase planning heuristic and simulated annealing algorithm to solve this problem. Grunow *et al.* [18] extended an idea of component sequencing to minimize the traveling time of the SMT machine head using operation planning in PCBA.

There is strong interdependency between different levels of the planning problem in PCB assembly and therefore, in literature different levels of the planning problems has been integrated and addressed. Hillier and Brandeau [19] designed a combined MILP model for LAP and CAP to reduce the net cost of the PCBAL. Furthermore, Gronalt and Zeller [20] integrate CAP and LAP to minimize the setup time and assembly time using heuristic approaches. Crama *et al.* [21] combined CPSP and LAP to focus on all distinct optimization problems related to PCB. Since all these three planning levels of PCBA are highly interrelated to each other. The solution of Level 2 problem influences the optimal solution of Level 3 problem and Level 2 problem is related to the solution of Level 1 problem. There is strong interdependency among all level problems in PCB assembly. However, in literature, all the three levels of planning problems have been investigated separately or with a combination of only two levels. Integration of planning and scheduling problems helps to make a unified space for the solutions, which consist of partial solutions for planning and scheduling of PCBAL. Therefore, multi-level planning and scheduling is required to solve three planning level problems simultaneously. Therefore, all these three levels of the problem are addressed simultaneously in the current research. Ji and Wan [22] reviewed the detailed literature about planning problems of PCBALs.

Since all these planning problems are NP-hard therefore heuristics [14], approximation methods [23], meta-heuristics [15] and constructive heuristics methods [24] have been developed to solve different planning level problems separately or combined. Moreover, CAPs have been solved in the literature using genetic algorithm [25], particle swarm optimization [10] and branch and bound algorithm [26]. Likewise, CPSPs have also been addressed in literature using local search [24], genetic algorithm [27] and shuffled frog leaping algorithm [13]. Swarm intelligent optimization algorithms are also useful to deal PCBAL problems. Lin and Huang [28] proposed a modified artificial bee colonial algorithm for assignment problem and placement sequences of components on PCB surface. Besides, spider monkey optimization (SMO) algorithm is a recently developed swarm optimization algorithm presented by Bansal *et al.* [29] which is designed to balance the exploration and exploitation effect to attain better optimization results for continuous planning problems. SMO is commonly applied to numerical optimization problem [29], [30] and preferred over other algorithms due to fast convergence rate [31]. However, hybridization in algorithm increases the performance of the actual algorithm for the specific problem type. Since the multi-level planning problems are complex because of dealing different problems simultaneously. To make SMO for discrete optimization problem and reduce the imbalance between exploitation and exploration motivate us to introduce hybrid SMO for the current problem by introducing new food sources and genetic operators in the original SMO respectively.

The novelty of current research is to consider multi-level planning and scheduling problems (LAP, CAP and CPSP) of parallel PCBALs simultaneously. Moreover, the empirical research problems are implemented to solve planning and scheduling problems simultaneously to maximize the net profit. Furthermore, hybrid spider monkey optimization (HSMO) algorithm is proposed first time for the discrete multi-level planning problem by introducing new food sources with integration of genetic operators (crossover and mutation) to make fast convergence and balance between exploitation and exploration. Therefore, the proposed HSMO outperform as compared to the original SMO.

The remainder of the paper is distributed as follows. Section 2 contains the current problem formulation and section 3 presents mathematical modeling. Section 4 describes the proposed hybrid spider monkey optimization (HSMO) algorithm to solve integrated multi-level planning and scheduling problem. Experimental design and computational results with analysis and discussions are elaborated in section 5 and section 6 respectively. In the last section, a brief conclusion of the research is extracted.

II. PROBLEM FORMULATION

In this section, a detailed description of a multi-level planning and scheduling problem of PCBALs is presented. The planning problem hierarchy for the PCB assembly is shown in the Figure 3. It can be seen from Figure 3 that the Level 1 of planning problem consists of the customer orders and assignment of different PCB boards to the assembly lines. In level 2 planning problem, the electronic components are assigned to the SMT machines in assembly lines and the component sequence is determined to place them on the surface of PCB boards in level 3. It is assumed that orders are fixed with known due dates and capacity of each line is different.

NOTATIONS

Notations used in the model are summarized as follows:

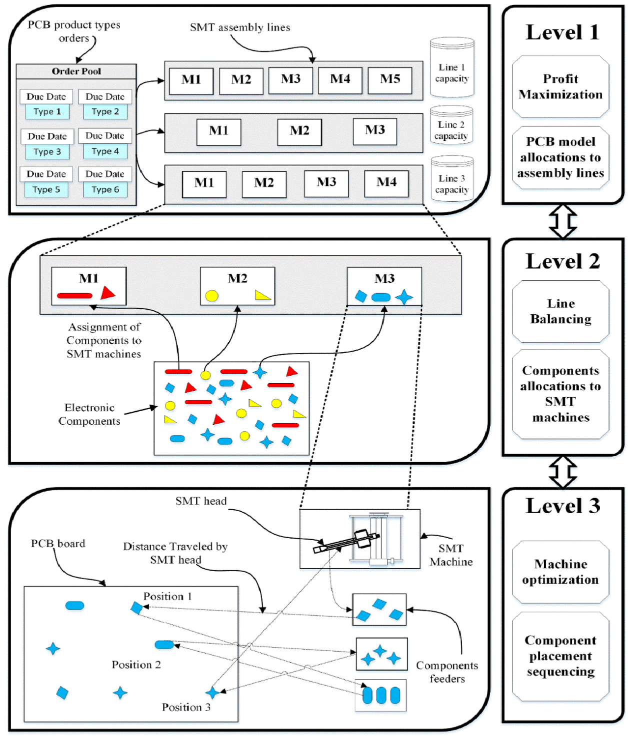

FIGURE 3. Planning hierarchy for PCB problem.

i	Index for SMT machines, $i = 1, 2, \ldots, I$
j	Index for PCB model types, $j = 1, 2, \ldots, J$
k	Index for types of components, $k = 1, 2, \ldots, K$
l	Index for SMT assembly lines $l = 1, 2, \ldots, L$
k_{ij}	Types of the components on machine i for PCB model j
NP_l	Net profit earned from assembly line l
UP_j	Unit profit value for PCB model j
UPC_j	Unit penalty cost for PCB model j
T_{jl}^c	Completion time of PCB j in line l
CT_{jl}^*	Optimum value of cycle time of line l for PCB j
CT_{jl}	Cycle time of assembly line l for PCB model j
CT_{jl}^x	Possible number of balancing solutions for cycle time of assembly line l for PCB j
x	Number of balancing solutions $x = 1, 2, \ldots., X$
n_j^k	Number of types of components for PCB model j
n^k	Number of types of components k
f	Feeder for component storage, $f = 1, 2, \ldots, F$
f_{il}	Feeder for components on machine i and assembly line l, $f_{il} = 1, 2, \ldots, F$
n_{ij}^k	Number of types of component at machine i for PCBj in an assembly line
n^f	Number of feeders in an assembly line
S^k	Set of different types of components
S_j^k	Set of components type k for PCB model j
S_{ij}^k	Set of component type k on machine i for PCB model j
SDP_{ijl}^*	The optimum value of sequence-dependent process time at machine i in assembly line l for PCB model j

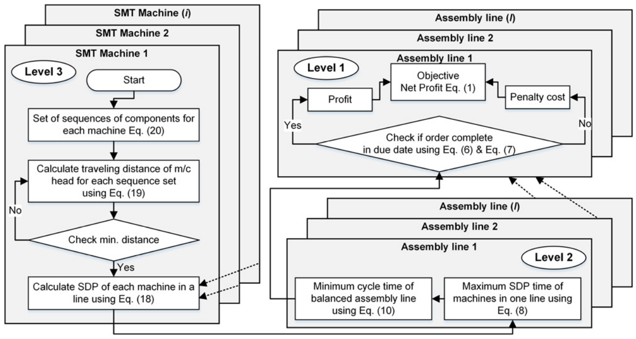

FIGURE 4. Integrated multi-level planning and scheduling methodology procedure.

SDP_{ijl}	Sequence-dependent process time for machine i on an assembly line l for PCB model j
$D\left\{\pi\left(k_{ij}\right)\right\}$	Distance traveled by machine head to place components with sequence $\pi(k_{ij})$ for PCB model j in the assembly line l
v	The velocity of head movement of machine i
$\pi(k_{ij})$	Set of sequences of components for PCB model j on machine i
n	Index for component sequence set number, $n = 1, 2, \ldots N$
$d_{0f_{il}}$	Distance covered by machine head from start point to feeder f_{il}
$d_{f_{il}b}$	Distance traveled by machine head from feeder f to component k'
$d_{af_{il}}$	Distance covered by machine head from component k to the feeder f
d_{a0}	Distance covered by SMT head from component k to the starting point
a, b	Index used for component position on PCB model, $a, b = 0, 1, 2, \ldots, n_j^k$
p	Index used for component position in the sequence set $\pi(k_{ij})$ of component placement in PCB model, $p = 1, 2, \ldots, n_j^k$
A	The limit value for smoothness index
SI_l	Smoothness index for assembly line l

III. MATHEMATICAL MODELLING

This section consists of mathematical modeling of above-mentioned integrated planning problems. Flowchart of the integrated solution of planning and scheduling procedure is shown in Figure 4.

A. LINE ASSIGNMENT PROBLEM (LAP)

Assignment of different type of PCB boards to different PCB assembly lines is discussed in this section. Number of SMT machines in each line defines the capacity of the line. Optimum assignment of PCB models to the assembly line is required to maximize the net profit by minimizing the sequence-dependent processing time.

$$Maximize\ Z = \left\{\sum_{l=1}^{L} NP_l\right\} \tag{1}$$

$$NP_l = \sum_{j=1}^{J} \left\{UP_j - Y_{jl} \times UPC_j\right\} \quad \forall l \tag{2}$$

$$T_{jl}^c = CT_{jl}^* \quad \forall j\, \forall l \tag{3}$$

$$J \leq L \tag{4}$$

$$\sum_{j=1}^{J} Z_{jl} \leq 1 \quad \forall l \tag{5}$$

Decision variables,

$$Y_{jl} = \begin{cases} 1 & dd_j - T_{jl}^c < 0 \\ 0 & otherwise \end{cases} \tag{6}$$

$$Z_{jl} = \begin{cases} 1 & if\ PCB\ board\ j\ is\ assigned\ to\ assembly\ line\ l \\ 0 & otherwise \end{cases} \tag{7}$$

Equation (1) indicates the objective function, i.e., maximization of the net profit from all PCB assembly lines. Equation (2) is used to calculate the net profit of each assembly line for allocated PCB board to the line. The first part is unit profit for that PCB board and the second part is the penalty cost applied if PCB board is delayed from the due date. Equation (3) indicates the completion time of PCB board in assembly line is equal to the cycle time. The difference between completion time and due date of the PCB board gives an indication that either finished PCB board is completed on time or it is delayed. Equation (4) ensures that the total number of types of PCB boards assigned to assembly lines must be less than the number of assembly lines. Equation (5) ensures that each line can only be assigned one type of PCB board. Equations (6) and (7) express the binary values of the decision variable used in the constraints and objective function.

B. COMPONENT ALLOCATION PROBLEM (CAP)

In CAP, it is significant to optimize the allocation of components to SMT machines. Moreover, the CAP is more related to balance the workload on all machines in the line and therefore, minimize the cycle time is significant in this problem. A mathematical model for this objective is formulated in (8).

$$CT_{jl} = \max\left\{SDP_{ijl}^*\right\} \quad \forall i\, \forall l\, \forall j \tag{8}$$

$$CT_{jl}^x = \left\{CT_{jl}^1, CT_{jl}^2, \ldots, CT_{jl}^X\right\} \quad \forall j\, \forall l \tag{9}$$

$$CT_{jl}^* = \min\left(CT_{jl}\right) \quad \forall j\, \forall l \tag{10}$$

$$Subject\ to: \sum_{i=1}^{I} f \geq n^k \quad k \in S_j^k \tag{11}$$

$$\sum_{j=1}^{J} n_j^k \leq n^k \quad k \in S_j^k \tag{12}$$

$$n^k \leq n^f \tag{13}$$

$$\sum_{k=1}^{K} Y^{kf} \leq 1 \quad \forall f \tag{14}$$

$$\sum_{f=1}^{F} Y^{kf} \leq 1 \quad k \in S_j^k \tag{15}$$

$$S_j^k \subseteq S^k \quad \forall k\, \forall j \tag{16}$$

$$Y^{kf} = \begin{cases} 1 & \textit{if component type } k \textit{ is} \\ & \textit{assigned to feeder } f \\ 0 & \textit{otherwise} \end{cases} \tag{17}$$

Equation (8) represents the cycle time which is considered as the workload of machines and obtained from level 3 problem. The machine which has maximum SDP time is considered as the bottleneck machine in the assembly line. Equation (9) contains different sets of components which are available to allocate to machines in an assembly line. Each set of the component provides unique balancing solutions. Among all the balancing solution, the minimum value of cycle time is selected and assigned as the optimum value of cycle time. Equation (10) indicates the optimum value of cycle time with balanced solution. Equations (11) to Equation (17) are constraints for CAP. Equation (11) ensures that the sum of feeders of all machines in assembly line must be greater than the number of types of components of PCB assigned to the assembly line. Equation (12) shows that the number of types of components required for all PCB models must be less than the total available number of types of components. Equation (13) assures that the number of types of components required for PCB model at each machine must be less or equal to the number of feeders available at machine because one feeder can store only one type of component. Equation (14) ensures that each feeder can contain only one type of component. Equation (15) ensures that each type of component can only be in one feeder at a time. Equation (16) indicates that the set of components types for a PCB model is a subset of the set of all available component types. Equation (17) is the decision variable to represent the binary variable conditions.

C. COMPONENT PLACEMENT SEQUENCING PROBLEM (CPSP)

The components which are allocated to machines for a PCB board are assembled on the PCB board using pick and place machine. The component placement time depends on the traveling distance of machine head to pick and place the components on PCB board on different position. In short, the processing time of placement of component depends on the sequence of placement of the components on PCB boards. The workload on machines is sequence dependent process time and it is required to minimize the traveling distance of the machine head for component placement. The optimum sequence is required to maximize the throughput by minimizing the SDP time. The optimum value of SDP time is illustrated in (18) and the constraints are presented in (19) to (28).

$$SDP_{ijl}^{*} = \min\left\{SDP_{ijl}\right\} = \frac{\min D\left\{\pi(k_{ij})\right\}}{v} \quad \forall i\, \forall l\, \forall j \quad k_{ij} \in S_{ij}^k \tag{18}$$

$$\begin{aligned} D\left\{\pi(k_{ij})\right\} &= \sum_{b=1}^{n_{ij}^k} \sum_{k_{ij}=1}^{n_{ij}^k} \sum_{f_{il}}^{F} \left(d_{0f_{il}} - d_{f_{il}b}\right) X_{b1}.Y_{k_{ij}f_{il}} \\ &+ \sum_{a=1}^{n_{ij}^k} \sum_{\substack{b=1 \\ b\neq a}}^{n_{ij}^k} \sum_{p=1}^{n_{ij}^k-1} \sum_{k_{ij}=1}^{n_{ij}^k} \sum_{f_{il}=1}^{F} \left(d_{af_{il}} - d_{f_{il}b}\right) \\ &\times X_{ap}.X_{b(p+1)}.Y_{k_{ij}f_{il}} + \sum_{a=1}^{n_{ij}^k} d_{a0}.X_{an_{ij}^k} \end{aligned} \tag{19}$$

$$n\pi(k_{ij}) = \left\{1\pi(k_{ij}), 2\pi(k_{ij}), \ldots, N\pi(k_{ij})\right\} \quad k_{ij} \in S_{ij}^k \quad \forall i\, \forall j \tag{20}$$

$$\sum_{a=1}^{n_{ij}^k} X_{ap} = 1 \quad \forall p \tag{21}$$

$$\sum_{p=1}^{n_{ij}^k} X_{ap} = 1 \quad \forall a \tag{22}$$

$$SI_l \leq A \quad \forall l \tag{23}$$

$$SI_l = \sqrt{\sum_{j=1}^{J} \sum_{i=1}^{I} \left(CT_{jl} - SDP_{ijl}\right)^2} \quad \forall l \tag{24}$$

$$X_{ap} = \begin{cases} 1 & \textit{if component } a \textit{ is placed at} \\ & p^{th} \textit{ position on PCB board} \\ 0 & \textit{otherwise} \end{cases} \tag{25}$$

$$X_{b(p+1)} = \begin{cases} 1 & \textit{if component position } b \textit{ is} \\ & \textit{placed in } (p+1)^{th} \textit{ postion} \\ 0 & \textit{otherwise} \end{cases} \tag{26}$$

$$X_{bf_{il}} = \begin{cases} 1 & \textit{if component at position } b \\ & \textit{is stored in feeder } f_{il} \\ 0 & \textit{otherwise} \end{cases} \tag{27}$$

$$Y_{k_{ij}f_{il}} = \begin{cases} 1 & \textit{if componet } k_{ij} \textit{ is available} \\ & \textit{in feeder } f_{il} \\ 0 & \textit{otherwise} \end{cases} \tag{28}$$

The optimum sequence is required to perform component placement in minimum time. Therefore, at this level, the cycle time of the assembly line is computed by the maximum SDP values of all machines at all possible components' sequences. Equation (18) is used to calculate the optimum value of SDP for each machine. Placement speed of machine head is assumed as constant for all machines because all machines are identical. Equation (19) is employed to calculate the traveling distance of machine head for each sequence of placement of components. Equation (20) indicates the sets of possible component sequences. The optimum sequence can be identified by calculating the traveling distances for each set of sequences. Equation (21) to (24) are the constraints for the sequencing of components problem. Equation (21) assures the placement of one component at only one position on the PCB surface. Equation (22) ensures the availability of single component for one position at PCB model. Equation (23) ensures the line balancing, i.e., the SDP of each machine in the line should close to the allowable limit. Equation (24) indicates smoothness index to ensure the cycle time deviation of assembly line and SDP of machines. Equations (25) to (28) are the binary decision variables adopted during calculation of constraints for CPSP.

IV. HYBRID SPIDER MONKEY OPTIMIZATION (HSMO)

Spider monkey optimization (SMO) algorithm is first time developed by Bansal *et al.* [29]. SMO is a swarm intelligent optimization algorithm inspired by social foraging behavior of a special type of monkeys known as spider monkeys (SMs). SMs fits in the class of fission-fusion social structure (FFSS) animals [30]. FFSS animals use their intelligent foraging behavior to find food sources (FS) in the form of groups. Each FS indicates the solution of an optimization problem, while the fitness value represents the nectar amount of the FS. The main structure of SMO contains three major phases called initialization phase, local leader phase and global leader phase. In the initialization phase the random swarms are introduced in the form of SMs groups. The global group has large number of SMs with one global group leader (GGL). The global group members are responsible to search FS and share their nectar amount information with the GGL using greedy selection. If the inertia exists i.e. the global group members gives similar results for specific number of cycles, then the GGL splits the global group into small local groups with local group leader (LGL) for each group. The division of global group is carried out in global leader decision (GLD) phase. The local group members are responsible to start foraging of FS and update the nectar amount information to their corresponding LGL in local leader decision (LLD) phase. All LGL transfer the information of nectar amount of food sources to GGL within their territorial boundaries to update their position in terms of optimized solution using greedy selection. There are two necessary control parameters to take appropriate decisions in the SMO known as global leader range (GLR) and local leader range (LLR). GLR and LLR are useful to minimize the inertia when GGL and LGL are unable to update their position after certain number of cycles. These phases of SMO work continuously until the termination criteria is satisfied.

The original SMO algorithm is appropriate to optimize the continuous problems. For example, Gupta *et al.* [33], [34] presented SMO for the constrained and non-constrained continuous optimization problem to check the performance of scalable and non-scalable problems. In the multi-level planning and scheduling problem, variety of PCB models available to assemble the electronic components in the assembly line; which indicates the discrete nature of the current problem. Therefore, the integrated multi-level planning and scheduling problem of PCB assembly line is different from the continues optimization problems discussed in the literature. In the original SMO each spider monkey is assigned single food source to explore the number of optimized solutions. To cope with current multi-level planning optimization problem, a new food source representation is required. This food source is introduced in SMO to improve the exploration by increasing the local search space of the algorithm. Therefore, a new hybrid SMO (HSMO) algorithm is proposed by introducing genetic operators (i.e. crossover and mutation) in simple SMO to generate new neighborhood food sources for each swarm of spider monkey to solve discrete multi-level planning optimization problem. The wide range of local search in HSMO helps to search the optimum solution. A detailed process flowchart of the proposed HSMO is shown in Figure 5 and step wise description is given in the next section.

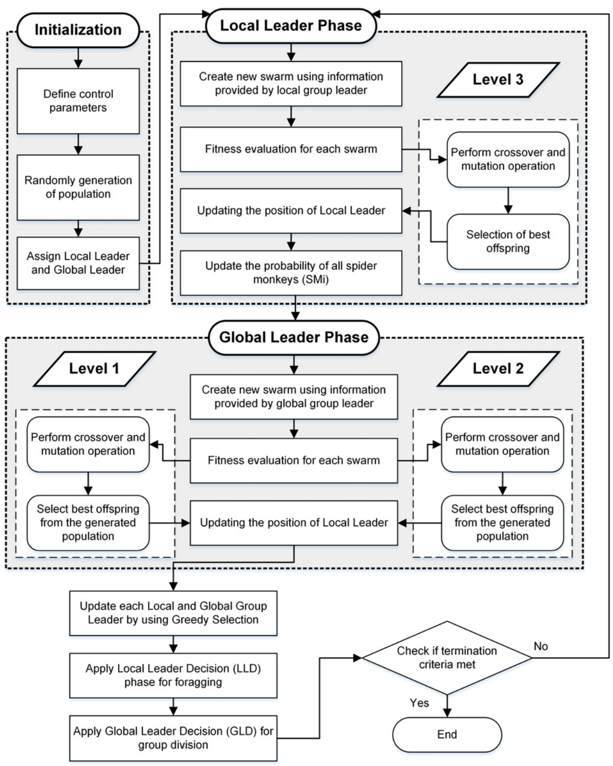

FIGURE 5. Flow chart of the proposed hybrid spider monkey optimization (HSMO) algorithm.

A. FOOD SOURCE REPRESENTATION

In current multi-level planning and scheduling problem, the food source representation composed of three parts and each part represents the individual planning problem. The first part of food source P1 represents the LAP, second part of food source P2 represents the CAP and third part of food

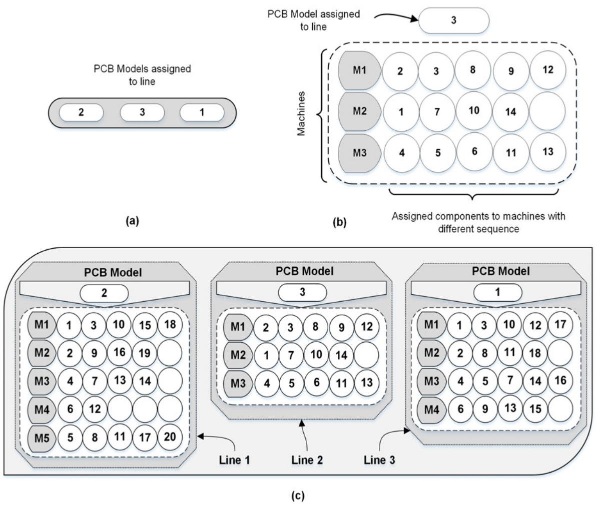

FIGURE 6. (a) Vector representation of first part P1 of food source containing PCB model sequence (b) Encoding example of second (P2) and third (P3) part of food source (c) Combined encoding strategy for all three parts of food source.

source P3 indicates the CPSP. The vector representation of P1 is shown in Figure 6(a). It can be seen from Figure 6(a) that the number of elements in the vector depicts the number of PCB board required to assign in assembly lines and their position in the vector shows their assignment sequence. It can be seen from Figure 6(c) that PCB boards are assigned to each line according to the defined sequence in P1 of food source. Therefore, the purpose of first part of FS is to find an optimum allocation sequence of the PCB boards to the assembly lines. The P2 of food source can be seen in Figure 6(b); each row indicates the SMT machines {M1 M2 M3} along with the allocated components {2 3 8 9 12}, {1 7 10 14} and {4 5 6 11 13} to each machine respectively. The purpose of P2 is to find an optimum component allocation by considering the workload balancing at each machine. Moreover, the P3 is related to CPSP, which is used to find the optimum component placement sequence. The allocated components in P2 are sequenced in P3 by considering the line balancing strategy. All the three parts of food source are illustrated in Figure 6(c) together to solve them simultaneously using proposed HSMO.

B. FOOD SOURCE INITIALIZATION PHASE

In the proposed HSMO, the population of part P1 of FS is generated randomly with the size equal to population of swarms of SMs. Each part of FS is assigned to a swarm of spider monkey and number of swards in population are equal to the defined parameters in the problem. Similarly, for P2 and P3 the food sources are generated randomly based on P1 requirements. An initial population of food source of 'N' spider monkeys is initialized in the form of vector as shown in Figure 6. Equation (29) is used to initialize the new food sources

$$SM_{ij} = SM_{\min,j} + r(0,1) \times \left(SM_{\max,j} - SM_{\min,j}\right) \quad (29)$$

where, $SM_{\min j}$ and $SM_{\max j}$ are minimum and maximum bounds respectively and r is a random number between 0 and 1 to initialize the population for each part of food source. SM_{ij} is the j^{th} dimension of the i^{th} spider monkey.

C. LOCAL LEADER PHASE

In this phase local leader is responsible to update the existing SM swarms generated in initialization phase. To achieve this objective a new alternate position is generated for each part of food source with the help of local leader. The fitness value of P3 part of food source is calculated for each swarm of SM. At this stage the genetic operators (i.e. crossover and mutation) are introduced in the simple SMO to generate new neighborhood FS for each swarm of SM which helps to increase the local group search space. To generate new FS a random binary selection vector is generated having the length equal to the number of types of electronic component assigned to the assembly line in the P3 part of the FS as shown in Figure 6. At this stage the component placement sequence is required to optimize based on the selection of best food sources. To improve the selection of best sequence for the component placement, the local search space of swarms is enhanced using genetic operators as discussed below.

Precedence preservative crossover (PPX) is applied to food source to share the information with each other. To understand the PPX procedure, an example is illustrated in Figure 7. Randomly generated binary selection vector is used to decide the selection of parent element for offspring. In random vector, 1 represents parent one and 2 indicates parent two elements will be selected for new offspring. For instance, the first element in the parent selection vector is 1, which means first parent's first element will be selected for the offspring, and so on. Similar operation is performed to all the elements and finally swap mutation operation is performed to generate final offspring with new food source as shown in Figure 7.

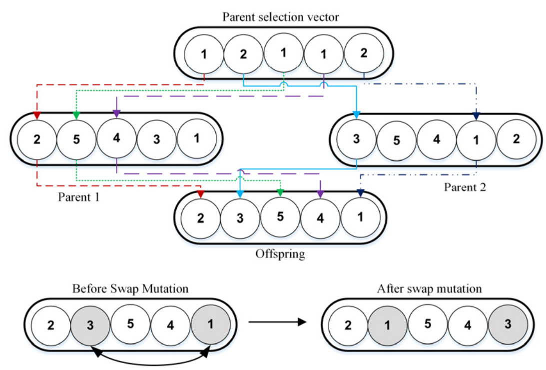

FIGURE 7. PPX crossover to create offspring.

The nectar amount of food source corresponding to the individual spider monkey is calculated in the form of fitness value. Greedy selection is applied at this stage to update the local group leader. The food source having maximum amount of nectar (fitness value) will be selected local group leader.

In this phase the selection of best food source means the best placement sequence of the components with minimum value of SDP time as discussed in the level 3 problem. In local leader phase, the position of food source is updated based on the experience of both local leader and their group members using (30).

$$SM_{ij(new)} = SM_{ij} + r(0, 1) \times (LL_{kj} - SM_{ij}) + r(-1, 1) \times (SM_{lj} - SM_{ij}) \quad (30)$$

where $SM_{ij(new)}$ is an updated position of food source, LL_{kj} shows the j^{th} dimension of the k^{th} position of local group leader. SM_{lj} is j^{th} dimension of the i^{th} spider monkey which is picked randomly from k^{th} group in such a way that $l \neq i$.

D. GLOBAL LEADER PHASE

In global leader phase, updating the existing swarm is responsibility of the global leader. Unlike the previous local leader phase, this phase deals with only single dimension of the selected solution of food source. That single solution is selected for update based on its probability which is calculated using (31).

$$prob_i = x \times \frac{f_i}{\max(f)} + y \quad (31)$$

Here, f_i is fitness value for the i^{th} swarm of spider monkey and max (f) is maximum fitness value. The sum of x and y is equal to one, after performing various experiments the optimum result of probability obtained at $(x, y) = (0.9, 0.1)$as explained by Sharma *et al.* [30]. The fitness values of the current solution and the previous one is compared and the best one will be adopted.

In the proposed HSMO, the global leader phase is dealing with two planning problems i.e., LAP and CAP. Therefore, the food sources P1 part and P2 are considered in global leader phase. P1 and P2 parts of food sources are dependent to each other because the components are allocated in the P2 depend on the PCB model assigned in the assembly line. After calculating the probabilities of the randomly generated parts of food source P1 and P2, the fitness values are evaluated. This fitness values indicates the nectar amount of each part of food source corresponding to the individual swarm of spider monkey in the global group. After calculating the fitness values of each swarm of the P1 part and P2 part of food source, the genetic operators are applied on both parts similar to the local leader phase. The food source having maximum amount of nectar will be selected as best among all the global group member. In this phase the selection of best food source means the best line assignment (P1 part) and best allocation of the components to the machines in assembly line (P2 part).

Greedy selection method is implemented at this stage to update the global leader. In this phase, the swarms having best fitness among all the group members will be upgraded as global leader of that group. If the fitness of any swarm is not updating, then it will remain same until global count limit. This process also known as global leader learning stage. The complete step wise description of proposed HSMO algorithm is shown in Figure 5. In global leader phase, the position of food source is updated using (32).

$$SM_{ij(new)} = SM_{ij} + r(0, 1) \times (GL_j - SM_{ij}) + r(-1, 1) \times (SM_{lj} - SM_{ij}) \quad (32)$$

where, GL_j indicates global leader in j^{th} dimension.

E. LOCAL LEADER DECISION PHASE AND GLOBAL LEADER DECISION PHASE

In this phase, the local leaders and global leaders of each group investigate the food sources received from local leader phase and global leader phase. In case of local leader decision phase, if the food sources are not updated in the defined limit then it will be performed again for the next cycle from the local leader phase. While, in case of global leader decision phase, if the food source P1 part and P2 part are not updated the global group leader will split the group into sub groups to minimize the stagnation and premature convergence.

V. EXPERIMENTAL DESIGN

As described in the literature section, the multi-level planning problem of PCB assembly line is novel and benchmark problems do not exist in literature. Therefore, the performance of the proposed HSMO is tested based on the real time generated benchmark problems instances for parallel PCB assembly line problems. Selection of the problem size is important because problem size is directly related to the computational time, performance and efficiency of the algorithm. To compute the best configuration of the proposed HSMO algorithm according to the given PCB assembly line problem, the design of experiment (DOE) method is used in this section. In the current problem, there are three factors which can decide the scale characteristics of the problem i.e., number of assembly lines (L), number of machines (M) and number of components (C). These factors are categorized in three levels based on the problem size, i.e., small, medium and large as given in Table 1. In order to design the different combinations of the problem sets, Taguchi factorial design of an orthogonal array (L9 (3^3)) is adopted. Here, L9 indicates the nine problem sets while 3^3 represents three factors for the considered problem having three different levels. Total nine problem sets are generated as given in Table 2. All PCB assembly line problem parameters (assembly lines, machines and components) are generated by uniform random distribution within predefined boundaries for each problem.

TABLE 1. Characteristics of test problem experiments.

Levels	Factors		
	L	M	C
Small	(2-4)	(2-4)	(20-40)
Medium	(5-7)	(5-7)	(50-70)
Large	(8-10)	(8-10)	(80-100)

TABLE 2. Test problem design.

Problem sets	L	M	C
1	(2-4)	(2-4)	(20-40)
2	(2-4)	(5-7)	(50-70)
3	(2-4)	(8-10)	(80-100)
4	(5-7)	(2-4)	(50-70)
5	(5-7)	(5-7)	(80-100)
6	(5-7)	(8-10)	(20-40)
7	(8-10)	(2-4)	(80-100)
8	(8-10)	(5-7)	(20-40)
9	(8-10)	(8-10)	(50-70)

The evaluation of results is concerned with the value of objective function for each test problem. The performance of the algorithm can be measured using various performance indicators; for example, convergence speed and robustness of solution. To evaluate the performance of the proposed HSMO algorithm, algorithm is tested on the above generated test problem instances and compared with four existing algorithms.

EXPERIMENTAL SETTINGS

There are total nine problem sets which are divided into three sizes based on the number of assembly lines. Problem sets {1, 2, 3}, {4, 5, 6} and {7, 8, 9} are named as small, medium and large size problem case instance. To estimate the performance of each parameter in all problem sets, 5 different replications are randomly generated for each problem set. Therefore, total 45 problem set case instances are used to evaluate the performance of the proposed algorithm and four existing algorithms. The proposed algorithm and compared algorithms are coded in Matlab and implemented on intel core i7, 3.4 GHz processor and 8 GB RAM computer. Moreover, the parametric tuning is performed using Taguchi method to find an optimum value of the objective function [35]. The optimum values of key parameters used for the proposed hybrid spider monkey optimization algorithm are summarized in Table 3. In the next section, computational results of proposed HSMO algorithm and compared algorithm are explained based on the experiments performed for all generated problem sets.

TABLE 3. Parameters used for proposed HSMO algorithm.

Parameters	Value
Swarm count (SC)	20
Maximum number of groups	10
Loop count (LC)	100
Food source population	200
Mutation rate	0.1
Crossover rate	0.9
Unit record time	0.5 sec

VI. COMPUTATIONAL RESULTS

In this section, the performance of the proposed HSMO algorithm is tested against some famous algorithms proposed in literature for PCB assembly line planning and scheduling problem: genetic algorithm [7], artificial bee colonial algorithm [36], particle swarm optimization algorithm [37] and simulated annealing algorithm [38]. To evaluate the effectiveness of the proposed HSMO algorithm, a detailed computation experiments are executed for detailed comparison with above mentioned literature algorithms. The test problems generated in the previous section are used to evaluate the performance of each algorithm at the defined key parameters in Table 3. Each test problem given in Table 2 are replicated five times to enhance the number of solutions and investigate the performance of the algorithms at various parameters. All algorithms are evaluated based on the computation time to achieve the optimum solution. The optimum and mean results of each problem set replicates after performing 100 iterations are given in the Table 4. There are different performance indicators to evaluate the efficiency of the algorithms. These performance measures include diversity in results, quality of result and convergence speed towards optimum solution. Besides, the performance of the algorithm can also be evaluated using averaged relative percentage deviation (ARPD) which is calculated by using the (33).

$$ARPD = \frac{C_{best} - C_{new}}{C_{best}} \times 100 \tag{33}$$

where C_{best} is the best solution obtained from complete problem set consist of all five replications and C_{new} is any new solution obtained from the same case instance. It is obvious that the smaller the value of ARPD, the better will be the proposed results because the maximization of objective function. Table 4 reports the comparison of optimum and ARPD results for the proposed HSMO algorithm and four compared algorithms on the premise of same experimental environment and key parameters. From the Table 4: (1) it can be observed that the ARPD values for the proposed HSMO algorithm is smaller as compared to the other algorithms; (2) the optimum value of objective function is maximum for the proposed algorithm. Moreover, the superiority of the proposed HSMO algorithm over the compared algorithm always significant for all problem sizes. From the Table 4, it can be concluded that the proposed algorithm can take advantage of genetic operators introduced to enhance the exploration capability of the spider monkey optimization algorithm. Therefore, the performance of the proposed HSMO algorithm is significantly superior to all compared algorithms. Furthermore, the performance of proposed algorithm over the compared algorithms is investigated in the next section based on different comparison criteria.

A. COMPARISON AMONG ALGORITHMS

The performance of the proposed HSMO algorithm and four compared algorithms is examined with maximum net profit value for each problem case instances generated in

TABLE 4. Optimization results of proposed HSMO and compared algorithms.

Problem Sets	Case No.	ABC		GA		PSO		SA		HSMO	
[L, M, C]		Opt.	ARPD	Opt.	ARPD	Opt.	ARPD	Opt.	ARPD	Opt.	ARPD
[(2-3), (2-4), (10-20)]	1	5769	0.447	5657	0.466	5241	0.535	5715	0.456	**6025**	**0.404**
	2	3554	0.815	3608	0.806	1568	1.144	2774	0.944	**4494**	**0.659**
	3	6366	0.348	6238	0.369	5276	0.529	6104	0.391	**7098**	**0.226**
	4	7868	0.099	8030	0.072	6950	0.251	7782	0.113	**8462**	**0.000**
	5	3546	0.816	3372	0.845	2798	0.940	3130	0.885	**3898**	**0.758**
[(2-3), (5-7), (21-30)]	1	13800	0.302	13742	0.305	13148	0.335	13568	0.314	**14062**	**0.289**
	2	6723	0.660	6723	0.660	6711	0.661	6723	0.660	**6723**	**0.660**
	3	15870	0.197	16038	0.189	14852	0.249	16174	0.182	**16882**	**0.146**
	4	17060	0.137	17274	0.126	16284	0.176	16710	0.155	**17434**	**0.118**
	5	19398	0.019	18642	0.057	17120	0.134	19152	0.031	**19772**	**0.000**
[(2-3), (8-9), (31-40)]	1	26578	0.197	26754	0.192	25074	0.243	26802	0.190	**27200**	**0.178**
	2	32607	0.015	32219	0.027	30865	0.068	32211	0.027	**33101**	**0.000**
	3	16351	0.506	16289	0.508	15895	0.520	16243	0.509	**16435**	**0.503**
	4	29060	0.133	28878	0.128	27758	0.161	28434	0.141	**28990**	**0.124**
	5	22031	0.334	21893	0.339	21555	0.349	21989	0.336	**22081**	**0.333**
[(4-6), (2-4), (21-30)]	1	24656	0.351	24374	0.358	21954	0.422	24094	0.366	**26176**	**0.311**
	2	32876	0.135	32676	0.140	29126	0.233	30020	0.210	**35504**	**0.066**
	3	23180	0.390	24154	0.364	19672	0.482	23170	0.390	**26866**	**0.293**
	4	36295	0.045	35675	0.061	32261	0.151	37053	0.025	**37993**	**0.000**
	5	19752	0.480	19806	0.479	16502	0.566	19862	0.477	**23376**	**0.385**
[(4-6), (5-7), (31-40)]	1	62618	0.101	61982	0.110	59010	0.153	62690	0.100	**63762**	**0.085**
	2	66482	0.046	66164	0.050	61072	0.123	66986	0.038	**69654**	**0.000**
	3	63608	0.087	63162	0.093	59626	0.144	64306	0.077	**65612**	**0.058**
	4	48624	0.302	48626	0.302	46832	0.328	49058	0.296	**50198**	**0.279**
	5	58707	0.157	58845	0.155	55945	0.197	58269	0.163	**61833**	**0.112**
[(4-6), (8-9), (10-20)]	1	28599	0.069	28791	0.062	25899	0.157	29629	0.035	**30709**	**0.000**
	2	13205	0.570	12949	0.578	11763	0.617	13613	0.557	**13721**	**0.553**
	3	17187	0.440	17197	0.440	15921	0.482	18407	0.401	**18423**	**0.400**
	4	19122	0.377	19012	0.381	17976	0.415	19162	0.376	**19954**	**0.350**
	5	17432	0.432	17240	0.439	16372	0.467	17700	0.424	**17858**	**0.418**
[(7-8), (2-4), (31-40)]	1	55462	0.276	56032	0.269	47266	0.383	54066	0.294	**62028**	**0.190**
	2	54528	0.288	55862	0.271	51208	0.332	51800	0.324	**58700**	**0.234**
	3	57331	0.252	56743	0.259	50695	0.338	55419	0.277	**61569**	**0.196**
	4	56479	0.263	56193	0.266	50361	0.343	54107	0.294	**60309**	**0.213**
	5	71288	0.069	72004	0.060	64384	0.160	70718	0.077	**76606**	**0.000**
[(7-8), (5-7), (10-20)]	1	22229	0.394	22247	0.394	18935	0.484	24331	0.337	**25321**	**0.310**
	2	21585	0.412	22367	0.391	19141	0.479	23577	0.358	**23973**	**0.347**
	3	27003	0.264	26653	0.274	24027	0.345	28181	0.232	**29975**	**0.183**
	4	20984	0.428	20906	0.430	19028	0.482	21262	0.421	**22492**	**0.387**
	5	34798	0.052	34570	0.058	31824	0.133	35490	0.033	**36708**	**0.000**
[(7-8), (8-9), (21-30)]	1	43981	0.089	43863	0.091	41227	0.146	44469	0.079	**45597**	**0.055**
	2	39870	0.174	39468	0.182	37142	0.230	40076	0.170	**41038**	**0.150**
	3	37857	0.216	37949	0.214	36239	0.249	38373	0.205	**38829**	**0.195**
	4	47337	0.019	47497	0.016	45219	0.063	47515	0.015	**48263**	**0.000**
	5	45378	0.060	44826	0.071	42614	0.117	46450	0.038	**46588**	**0.035**

the previous section. The purpose of the comparison of proposed algorithm with previous literature algorithms is to validate the performance and effectiveness of the algorithms. All the problems sets are tested to evaluate the net profit under all defined assumptions and constraints with carefully implementation of algorithms. The computation time is taken as the termination criteria for all the algorithms to find the optimum value of net profit. After testing all the

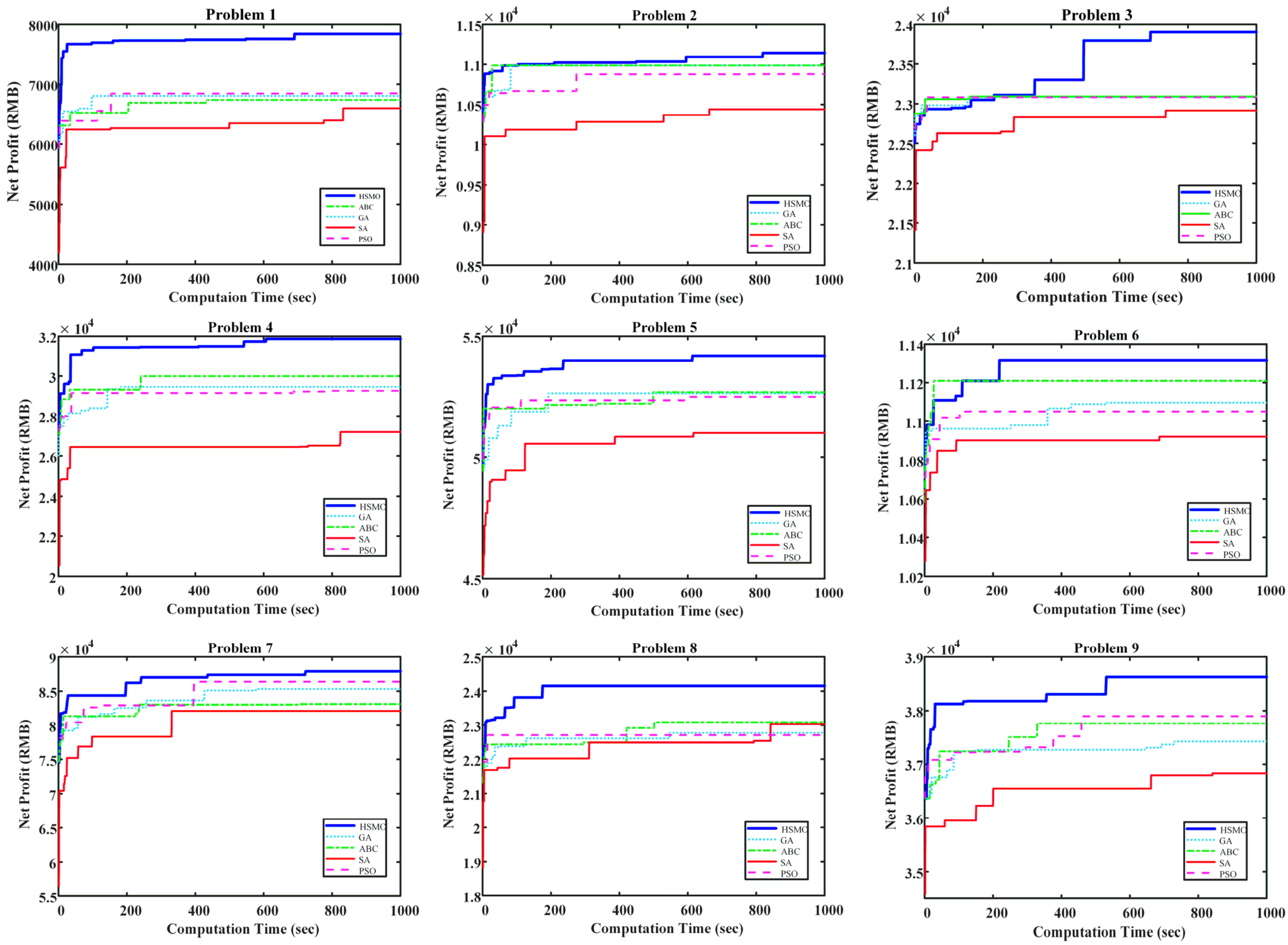

FIGURE 8. **Convergence curves for computation time and net profit; Problem (1-3) for small size problem sets, Problem (4-6) for medium size problem sets and Problem (7-9) for large size problem sets.**

algorithms at 1000 seconds computation time, the optimum results obtained from algorithms on each problem set are given in Table 4. It can be noted that, in Table 4 the results obtained by the proposed HSMO algorithm always maximum as compared to other algorithms' results which indicate that HSMO outperforms against the compared algorithms. For instance, in problem set 1, the optimum value of net profit for ABC, GA, PSO, SA and HSMO are 5769, 5657, 5241, 5715 and 6025 RMB respectively, which indicates that proposed HSMO algorithm perform better than all compared algorithms.

1) PERFORMANCE COMPARISON OF ALGORITHMS BASED ON THE CONVERGENCE

The performance results based on the convergence speed of solutions with respect to computation time of each algorithm are investigated in this section. The optimum results of the objective function are evaluated by using proposed algorithm and compared algorithms for the specific period to investigate the performance and convergence speed. In the current case, performance of all algorithms is investigated at 1000 seconds computation time as a termination criterion. The optimum value achieved at every 0.5 second is observed to investigate the time at which the convergence of algorithm stops. After settings key parameters (given in Table 3) of algorithms, proposed and compared algorithms are tested on all problem sets generated in the previous section. The graphical results of all nine problem sets obtained after executing each algorithm for 1000 seconds are shown in Figure 8. As each problem set contain five replications named as cases, so case 5 is taken from each problem because case 5 is considered as hard problem due to the complexity. Therefore, it is helpful to investigate the performance of each algorithm based on their convergence speed and optimum results with respect to computation time.

As all the test problem case instances are maximization problems; therefore, the greater fitness values correspond to good solutions. For instance, graphs in Figure 8 illustrates the comparison of algorithms based on convergence trend of nine problem sets for 1000 seconds run using proposed HSMO, ABC, GA, PSO and SA algorithms. It can be seen in Figure 8 that proposed algorithm found with maximum profit and high convergence rate. Moreover, it can also be observed from the graphs that in most of problem sets; ABC, GA, PSO and SA algorithms do not find the better solution as compared to the proposed HSMO algorithm. Hence, from Figure 8, it can be concluded that HSMO is best for all size of PCBAL problems because of high degree of accuracy of solutions with fastest convergence rate. HSMO perform more faster to achieve the best results in very short time and converge the solution towards optimal point till the termination criteria met. While, the convergence of the other algorithms i.e., ABC, GA and PSO is also fast in start but stopped convergence specific time. SA algorithm is different from the other compare algorithms because it operates according to annealing process and it can also select bad solutions. Therefore, the SA solutions in all the problem are not consistent and stable but the convergence speed of SA is very less as compared to other algorithms. It can be seen from the Figure 8 that although ABC, GA and PSO algorithms gives fast convergence of the solution but the optimum results of the proposed HSMO algorithm are better because of the more exploration. In the start, the convergence rate of HSMO algorithms is less but with the passage of the time, convergence rate is accelerated towards the optimum solution with proportional to the number of iterations performed. Similarly, ABC, GA, PSO and SA algorithms also indicate the fast convergence, but their convergence does not show the proportional behavior with computation time as shown in Figure 8.

Furthermore, it can be seen in Figure 8 that HSMO always give best optimum result for all problem sets. For instance; in problem 1, HSMO has achieved 7841 RMB profit, while GA, PSO, ABC and SA achieved 6805, 6847, 6739 and 6599 RMB respectively which shows that HSMO outperform against all compared algorithm. Moreover, the results of different algorithms can also be observed with respect to the computation time. For instance; in problem 1, most of algorithms achieved their optimum solution at near the 300 seconds, at this point the net profits for HSMO, GA, PSO, ABC and SA are 7733, 6805, 6843, 6691 and 6262 RMB respectively. A significant difference in the net profit value is observed between HSMO and all compared algorithm. Moreover, the PSO, GA and ABC achieved their optimum results before 300 seconds and there is no further improvement of solution is observed and the results of SA algorithm are also stable but with slow converge rate as compare to other algorithms. On the other hand, HSMO achieved better result than all other compared algorithm at nearly 300 seconds, which shows that the HSMO algorithm have less chance of trapping in local optima during the improvement in global optima. Similar trend is observed in all size of problem sets shown in Figure 8. This characteristic indicates that the proposed HSMO algorithm outperforms and achieve better results as compared to ABC, GA, PSO and SA algorithms. Therefore, the performance of HSMO with respect to convergence is superior than other algorithms and results demonstrate that exploration of HSMO is very effective.

2) PERFORMANCE OF ALGORITHMS BASED ON THE ROBUSTNESS OF SOLUTION

To verify the performance and effectiveness of the proposed HSMO algorithm, robustness of the solutions for each problem set is investigated in this section. For this purpose, each algorithm is run for 100 iterations. For each problem set, algorithms are run 20 times for 100 iterations and mean values are calculated for each solution. These mean values are used to investigate the robustness of the solutions as shown in Figure 9. One case problem is taken from each problem size sets replica to identify the robustness of optimized solutions. There are total nine mean value plots and each plot represent mean solutions values in one problem set. From the mean box plots in Figure 9, it can be observed that the proposed HSMO algorithm always outperform against the compared algorithms for all size of problem sets. Moreover, it can be seen in Figure 9 that mean and median values of net profit obtained from the proposed HSMO algorithm are always higher than the other compared algorithms. The solutions obtained from the HSMO algorithm are close to each other which indicates the robustness of solutions. In all problems the robustness of HSMO is stable and for ABC, GA, PSO and SA mean values of solution indicates that their solutions are not robust and vary with the increasing the number of iterations and computation time which shows the divergence behavior of the solutions. The solution obtained from ABC, GA and PSO also shows high robustness while the SA shows more divergence in the solutions. In general, any metaheuristic performs two main searching capabilities (Exploration and Exploitation). In this study, the proposed HSMO algorithm and compared algorithms i.e., ABC, GA and PSO are Population based algorithms which performs both exploration and exploitation while SA algorithm is a signal-based algorithm which perform only exploitation. Therefore, deficiency in exploration increases the chance of trapping the solution in local optima and robustness of the solution also decrease. ABC algorithm also perform with good robust solutions, but the proposed algorithm gives best solution in less time and in lesser number of iterations because of the hybrid nature of HSMO due to genetic operators. The genetic operators increase the exploration property and search more optimum solution. Due to this reason the solutions of HSMO gives high solution. Due to this reason the solutions of HSMO gives high value of net profit as shown in Figure 9. The fluctuation in robustness indicates that the results are not stable to find an optimum solution.

Furthermore, the error points in the plots in Figure 9 indicate the diversity of the solutions away from the optimum and mean values. It can be observed from Figure 9 that HSMO algorithm have few error points and near to the mean value. On the other hand, for the other four compared algorithms the error points are more and far from the mean point which indicates the disturbance in solutions. Therefore, it can be analyzed that proposed HSMO algorithm gives stable and more optimum solution in minimum number of iterations and

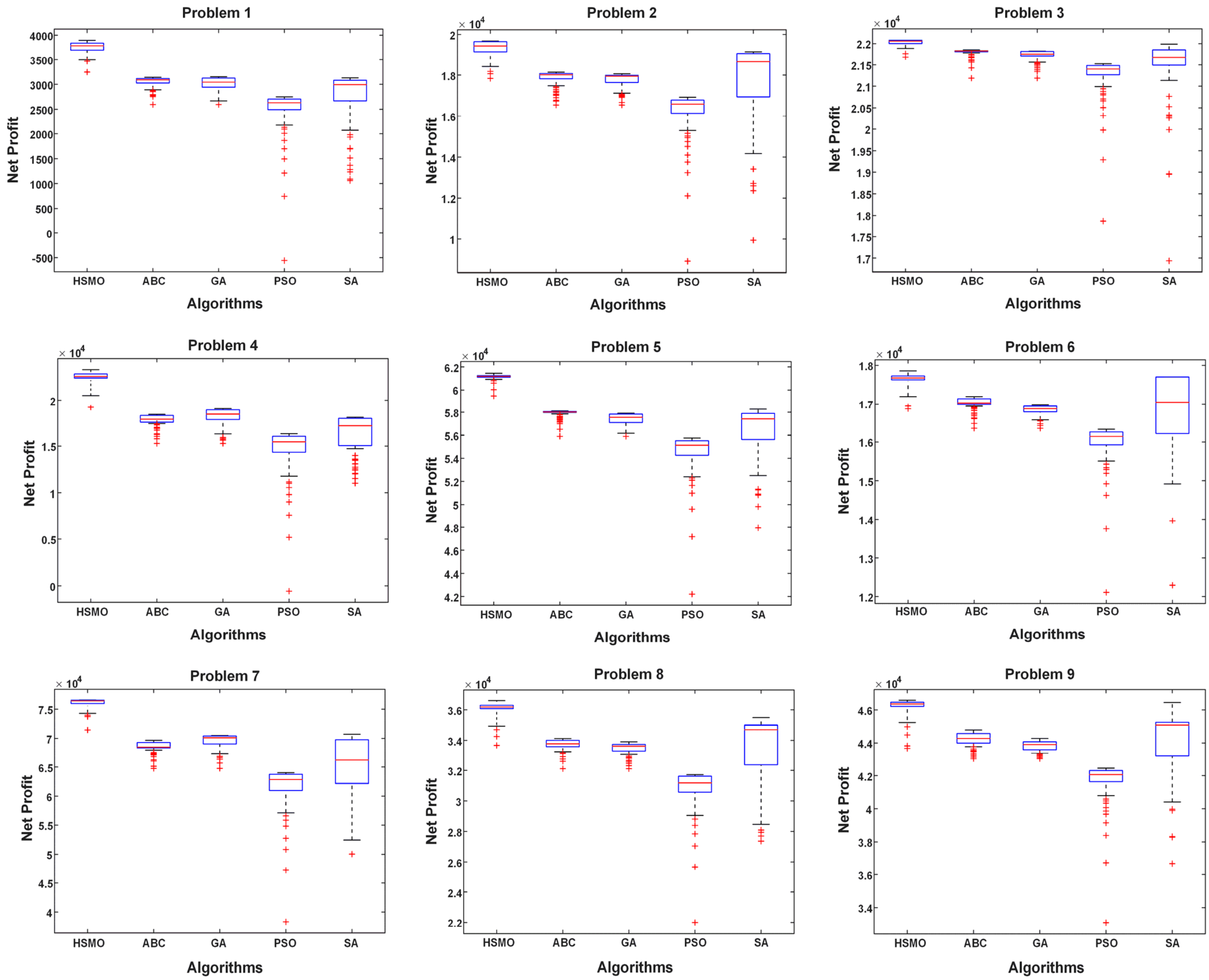

FIGURE 9. Boxplots for robustness of solutions; Problem (1-3) for small size problem sets, Problem (4-6) for medium size problem sets and Problem (7-9) for large size problem sets.

less computation time. Moreover, minimum variation in the mean value shows more reliability of the results of algorithm for that problem. Higher the mean value indicates more the net profit; therefore, from all the above comparison of results, it can be concluded that HSMO always outperforms against the four compared algorithms. To verify all these performance indicators in real time problem a case study problem is presented in the next section.

B. CASE PROBLEM

Multi-level planning and scheduling problem of a PCB manufacturing company in China is selected to investigate the performance of the proposed HSMO algorithm and compared algorithms to optimize the net profit. Two parallel PCB assembly lines are selected (Line 1 and Line 2) for two different PCB models (model A and model B) which are available to assign to the assembly line. Both assembly lines consist of four SMT machines to assemble different

TABLE 5. Initial population results.

Machine No.	Component type assigned		Component sequence	
	Line 1	Line 2	Line 1	Line 2
1	2,7	5,4	6,9,3,7,12,13,17	2,8,20,23
2	1	7,2	8,14,19,20	5,7,11,22,13,14,16, 1
3	8,6	3,1	2,4,10,11	15,18,4,6,9,10,19, 21,25
4	4,5,3	8,6	1,5,18,15,16	1,12,3,17,24

electronic components to the PCB surface. Both PCB models required eight different types of component with total quantity of 20 and 25 components for model A and B

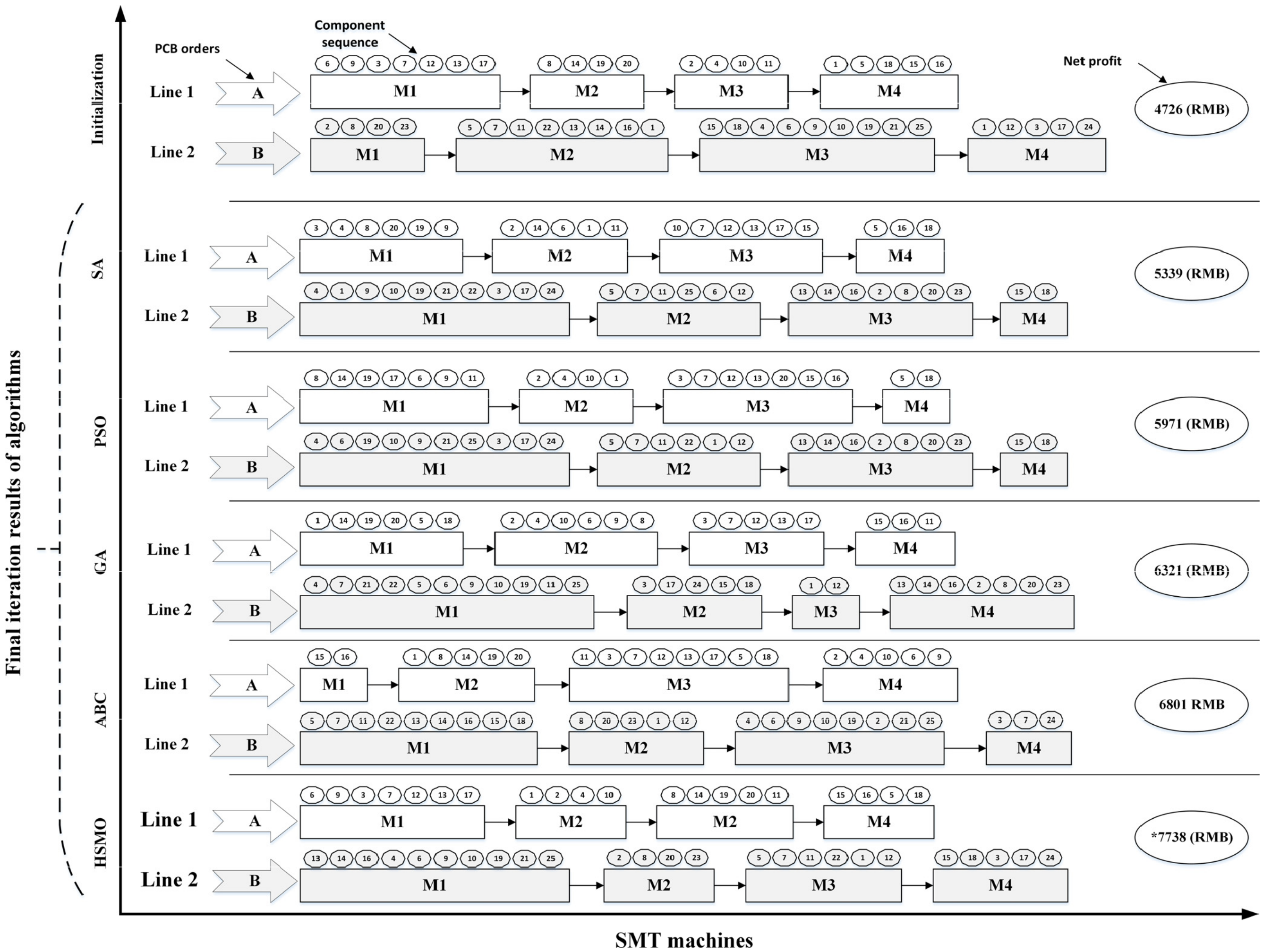

FIGURE 10. Case problem results of multi-level planning problem of PCBALs for proposed HSMO and compared ABC, GA, PSO and SA algorithms.

TABLE 6. Optimum allocation of components to both lines in sample problem using different algorithms.

Machine No	GA		PSO		ABC		SA		HSMO	
	Component types		Component type		Component type		Component type		Component type	
	Line 1	Line 2	Line 1	Line 2	Line 1	Line 2	Line 1	Line 2	Line 1	Line 2
1	1,2,6	1,6	1,5	7,1	3	2,3	1,3,4	6	2,7	2,1
2	8,4	7,8	8,2,4	6,3	4,1	4,7,8	2,8	2,6,7	4,8	5,4
3	7,3	2,5,4	7	8	6,7,5	1,5	5,6	1,5	1,6	7,8
4	5	3	3,6	2,5,4	8,2	6	7	3,4	3,5	3,8

respectively. In the initial population same sequence of the components is assigned for all algorithms to start them from same initial solution. The initially assigned components types to the machines in assembly line and component placement sequence to the PCB surface are given in the Table 5.

After performing all iterations, the final optimum allocation of components using different algorithms are given in Table 6 and optimum component placement sequence of the components are illustrated in Figure 10. Figure 10 is the schematic diagram of parallel assembly lines of PCB industry, in which initialized, and end results of the net profits are illustrated. It can be seen from the results in Figure 10 that the proposed HSMO outperforms against the four compared algorithms as net profit value is higher.

VII. CONCLUSION

In this paper, multi-level planning and scheduling problems of parallel PCBAL is studied with an objective function of net profit maximization. The importance of multi-level planning and scheduling problem for parallel PCBALs and lack of research literature in this area are the motivation behind this research. A mathematical model is formulated for the integrated planning and scheduling problems, i.e., (LAP, CAP and CPSP) based on logic and statistical interpretation. A new hybrid spider monkey optimization (HSMO) is proposed to optimize the current NP-hard problem. New real time benchmark problem instances are generated for the novel integrated planning problems of PCB assembly line. The computation experiments are performed to analyze the performance of the proposed HSMO algorithm based on convergence and robustness of the final solutions. The results reveal that the proposed HSMO outperforms against ABC, GA, PSO and SA algorithms. Furthermore, a real-time industry case problem for parallel PCBAL is investigated with an integrated planning and scheduling problem to validate the performance of the proposed HSMO algorithm.

In future research, multi-level planning and scheduling problem scheme can be extended for multi-objective and mixed model PCBAL problems simultaneously.

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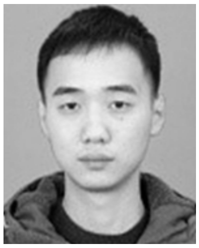

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